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Accruals and future performance: can it be attributed to risk?

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Abstract

We decompose broad based measures of accruals into firm specific and related firm components. We find that the negative relation between accruals and future firm performance is almost entirely attributable to the firm specific component. Standard risk based explanations are hard to reconcile with this fact. To the extent expected returns have a common component spanning related firms, a risk based explanation would suggest a stronger negative relation between accruals and future firm performance when related firms are also growing. Instead, the attenuation we document is more likely attributable to sub-optimal investment decisions, which the stock market and analysts do not incorporate in a timely manner.

JEL classification: G12; G14; M41
Key words: investment activity, accruals, profitability, stock returns, supply chain.

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1. Introduction

In this paper we revisit the negative relation between accruals and future firm performance. Past research has offered a variety of reasons for this negative relation. Sloan (1996) documents that the accrual component of earnings is less persistent than the cash flow component of earnings. Sloan then suggests that this differential persistence in earnings components explains the negative relation between accruals and future firm performance. Subsequent research has offered a variety of alternative competing explanations for this negative relation: (i) diminishing marginal returns to new investment (e.g., Fairfield, Whisenant and Yohn, 2003; Richardson, Sloan, Soliman and Tuna, 2006; and Zhang, 2007), (ii) accounting distortions and earnings management (e.g., Xie, 2001, Richardson, Sloan, Soliman and Tuna, 2005), (iii) risk (e.g., Kahn, 2008; Wu, Zhang and Zhang, 2010; Cooper and Priestley, 2011), and (iv) transaction costs (e.g., Mashruwala, Rajgopal and Shevlin, 2006).

Our focus is on the risk based explanation for the negative relation between measures of accruals and future firm performance. Cochrane (1991), Zhang (2005), Fama and French (2006), Wu, Zhang and Zhang (2010) and Cooper and Priestley (2011) all argue that firm investment decisions are rational responses to temporal variation in expected rates of return. When expected returns are low this should lead to higher levels of investment, and the observed lower future stock returns are a consequence of lower expected returns. This 'risk based' explanation fits perfectly with the well-known negative relation between measures of accruals and future firm performance. However, the explanation as offered does not allow for empirical falsification.

To be able to falsify a risk based explanation for the negative relation between accruals and future firm performance, we need to identify an implication of the risk based explanation that offers a new testable empirical prediction. Fortunately, there is an obvious candidate. A key determinant of expected returns is the combination of operating and investing decisions that management make to pursue a given (risky) business model. Firms operating in the same 'industry' are therefore likely to face very similar sources of systematic risk. Indeed, past research has looked to document expected returns and cost of capital at the industry level (e.g., Fama and French, 1997). Thus, by decomposing measures of accruals into a 'common' component shared by similar firms and a 'firm specific' component that is unique to each firm, we are able to assess the relative importance of risk based explanations for the negative relation between measures of accruals and future firm performance.

We additively decompose broad based measures of accruals (i.e., change in net operating assets, or ΔNOA) as follows. First, we identify related firms based on common industry membership and shared industry level supply chains. Second, we compute the average level of ΔNOA for these related sets of firms (i.e., $\Delta NOA^{RELATED}$). Third, we compute the firm specific portion (i.e., ΔNOA^{FIRM}) as the difference between ΔNOA and $\Delta NOA^{RELATED}$. The risk based explanation suggests that the negative relation between ΔNOA and future firm performance should be particularly strong for the common component ($\Delta NOA^{RELATED}$). If managers are rationally responding to time variation in expected returns, then this should be observed by other managers facing similar sources of systematic risk. In contrast, a non-risk based explanation that entertains the possibility of sub-optimal decision making by management, suggests that the negative relation between broad based measures of accruals and future firm performance should be evident in the firm specific component of accruals (i.e., the negative relation between accruals and future firm performance is expected to be stronger, after controlling for related firm growth).

For a sample of 766,496 US firm-months over the 1988-2010 period, consistent with past research, we find that ΔNOA is reliably negatively related with future firm performance (the full sample regression coefficient on ΔNOA in a standard ROA forecasting regression is -0.069). When we split ΔNOA additively into its components (i.e., ΔNOA^{FIRM} and $\Delta NOA^{RELATED}$), we find that the majority of the negative relation is attributable to ΔNOA^{FIRM}. This result holds for further decompositions of ΔNOA into current accrual measures (i.e., change in working capital, ΔWC) and non-current accrual measures (i.e., change in non-current net operating assets, ΔNCO). These differences are strongly significant at conventional levels. We further find that the negative relation between broad based measures of accruals and future stock returns is attributable to ΔNOA^{FIRM}. We find that the magnitude of the negative relation between ΔNOA^{FIRM} and future stock returns is three to four times as large as the negative relation between $\Delta NOA^{RELATED}$ and future stock returns. These differences are strongly significant at conventional levels. Finally, we find that sell-side analysts are slow in incorporating the information contained in ΔNOA into their earnings forecasts. In particular, analyst revisions are slow for the components of ΔNOA that have the strongest association with future stock returns, a finding that is difficult to reconcile with a risk based explanation for the negative relation between broad based measures of accruals and future returns.

We also decompose the information content of $\Delta NOA^{RELATED}$ into 'peer' firms (i.e., related firms in the same industry, labelled as ΔNOA^{PEER}) and 'non-peer' firms (i.e., related firms in different industries, but similar supply chains, labelled as $\Delta NOA^{NON-PEER}$). This is also an additive decomposition ($\Delta NOA^{RELATED} = \Delta NOA^{PEER} + \Delta NOA^{NON-PEER}$). We find some evidence of a negative relation between ΔNOA^{PEER} and $\Delta NOA^{NON-PEER}$ and future firm profitability, but no evidence of any negative relation between ΔNOA^{PEER} or $\Delta NOA^{NON-PEER}$

and future stock returns. This lack of a relation is hard to reconcile with a risk based explanation for the general negative relation between measures of accruals and future firm performance. Expected returns do vary through time and management investment decision may well vary rationally in response to that time variation in expected returns (e.g., Fama and French, 2006 and Wu, Zhang and Zhang 2010). When required returns are lower, the feasible investment set increases and, at the margin absent any frictions, managers will invest more. Thus, any ex post negative relation between investment activity and stock returns can be attributed to risk. However, it is most likely that there would be commonality in these expected return dynamics with similar firm's facing similar changes in their investment opportunity sets. Our empirical results are at odds with this prediction. The negative relation between measures of accruals and future stock returns is weakest for the common component of accruals and strongest for the firm-specific component of accruals.

Our results are related to past research. First, Dechow, Sloan and Sweeney (1995) introduced a simple industry model for 'normal' accruals. Second, a lot of research following from Jones (1991) estimate cross-sectional regressions by industry and use the resulting regression residual as a measure of abnormal accruals (e.g., Xie, 2001 and Francis, LaFond, Olsson and Schipper, 2005). Third, more recent research has started to use performance matching to estimate 'abnormal' accruals, and part of the matching criteria is industry membership (e.g., Kothari, Leone and Walsley, 2005). Collectively, this past research has incorporated industry membership to models of expected accruals. However, this past research has not (i) expressly considered the differential relation between sub-components of accrual measures and future stock returns, and (ii) linked these differential results to risk based explanations for the negative relation between measures of accruals and future stock returns.

We are obviously not the first to examine risk based explanations for the negative relation between measures of accruals and future returns. Past research has argued both for a risk based explanation (e.g., Khan, 2008 and Wu, Zhang and Zhang, 2010) and against a risk based explanation (e.g., Hirshleifer, Hou and Teoh, 2012). Our findings are consistent with Hirshleifer, Hou and Teoh (2012), but differ in several key respects. First, we consider a broad based measure of accruals, capturing total investment activity, rather than just the change in non-cash working capital. Second, we consider a specific risk based explanation, 'q-theory'. Given recent research (e.g., Wu, Zhang and Zhang, 2010 and Huang, Lam and Wei, 2014) has asserted that the negative relation between measures of accruals (and investment) is due to time varying expected returns as described in 'q-theory', it is important to analyse this specific explanation fully to assess how reasonable an explanation it is for the accrual anomaly.

Our analysis is also related to recent research examining how information travels along the supply chain. For example, Menzly and Ozbas (2010) find that knowledge of the supply chain linkages between industries is useful to generate superior forecasts of firm performance. Specifically, Menzly and Ozbas document a lagged response between downstream and upstream industry relative performance. Likewise, Cohen and Frazzini (2008) show that knowledge of firm-level customer-supplier relations is also useful to form superior unconditional forecasts of firm performance. Our empirical analysis is *not* simply the unconditional supply chain linkages examined in these papers, nor a pure industry momentum effect as in Moskowitz and Grinblatt (1999), as we control for the recent stock returns of related firms directly.

The rest of the paper is structured as follows. Section 2 describes our sample selection and research design. Section 3 presents our empirical analysis and robustness tests, and section 4 concludes.

2. Sample and research design

2.1 Identification of related firms and investment activity of related firms

We identify related firms based on industry level attributes. We focus our empirical strategy on industry level linkages as we expect substantial commonality in the operating, investing and financing decisions of firms that operate in the same industry grouping and supply chain. This commonality in operating, investing and financing decision making is the basis for shared exposures to systematic sources of risk that give rise to expected returns.

We identify economically related groups of firms based on common industry membership and shared industry level supply chains. We use the industry classifications in the Benchmark Input-Output Surveys of the Bureau of Economic Analysis (BEA Surveys). The BEA surveys are updated every five years and are labelled with a ‘look back’. As we describe in appendix I, we are careful to ensure that our use of the data in the BEA tables ensures that we are only using data that would have been known ‘point in time’. The first BEA table we use is from 1982 and there are 79 industries in those tables. The last BEA table we use is for 2002 and it contains 128 industry groups. In unreported analyses, we have looked at alternative industry groupings including 2 digit SICs and the 47 industry groupings in Fama and French (1997). Appendix I provides a full description of how we extract those measures. We are thus able to separately examine related firms into two mutually exclusive categories: (i) ‘peer’ firms, and (ii) ‘non-peer’ firms. Peer firms are those identified solely on the basis of common industry membership, and ‘non-peer’ firms are those identified by explicit industry level customer-supplier linkages.

The 'risk based' explanation for the negative relation between measures of accruals and future firm performance stems from the 'q theory' of investment. Our broad based measures of accruals are therefore designed to capture the totality of investment expenditures of firms. Specifically, we compute the change in net operating assets over the previous twelve months scaled by average total assets for each firm, which we label ΔNOA. We measure ΔNOA as in Richardson, Sloan, Soliman and Tuna (2005). Our first decomposition of ΔNOA is as follows:

$$\Delta NOA = \Delta NOA^{FIRM} + \Delta NOA^{RELATED} \tag{1}$$

To estimate $\Delta NOA^{RELATED}$ we average industry level investment activity over the previous twelve months using the weights implied by the I x I industry level input-output table. In our tabulated results we estimate industry level investment activity using total assets as weights, but our results are unchanged if we instead use equal weighting. ΔNOA^{FIRM} is then the difference between ΔNOA and $\Delta NOA^{RELATED}$. We have examined alternative measures of investment activity as suggested by Cooper and Priestley (2011), namely (i) percentage growth in total assets, (ii) percentage growth in net operating assets, or (iii) percentage growth in investment expenditure. We find similar results with these alternative measures of investment activity. It is also noting that our decomposition of ΔNOA into a related firm and firm specific component, is similar to the within and across industry decomposition of measures of value and momentum examined in Asness, Porter and Stevens (2000). They generally find stronger return predictability for the within industry component but do not link that finding to risk based explanations for the observed effects.

For our second decomposition of ΔNOA we also use the BEA survey data as follows:

$$\Delta NOA = \Delta NOA^{FIRM} + \Delta NOA^{PEER} + \Delta NOA^{NON-PEER} \tag{2}$$

Where $\Delta NOA^{PEER} + \Delta NOA^{NON-PEER} = \Delta NOA^{RELATED}$.

For both decompositions, we use the weights implied by the $I \times I$ industry level input-output table, to estimate the average investment activity of related firms. For example, using the sector input-output table described in Appendices I and II, firms in the agriculture, forestry, fishing and hunting sector (labelled as AGRIC.) are assigned a measure of investment activity of related firms based on (i) 31% of the investment activity of other agriculture, forestry, fishing and hunting firms, (ii) 62.7% of the investment activity of firms in the manufacturing sector, and (iii) the remaining 6.3% attributable to the investment activity of firms in the other industries with non-zero cells in the top row of the matrix in Appendix II. Thus, for the agriculture, forestry, fishing and hunting sector, ΔNOA^{PEER} is based solely on the investment activity of other agriculture, forestry, fishing and hunting firms, and $\Delta NOA^{NON-PEER}$ is based on the remaining industries that are economically connected to the agriculture, forestry, fishing and hunting sector. Thus, for each industry we compute the sum-product of the respective row in the input-output table and the vector of ΔNOA averages for each industry, and separately examine the diagonal and off-diagonal elements of the input-output table. The shading of cells in Appendix II reflects the strength of the industry level input-output linkages, with the darker cells reflecting the stronger linkages.

2.2 Our empirical tests

We conduct three sets of empirical analyses. First, we assess whether the negative relation between broad based measurers of accruals and future firm profitability varies across related and firm specific components. Second, we assess if the negative relation between broad based measurers of accruals and future stock returns varies across related and firm specific components. Third, we assess whether sell-side analysts efficiently *combine* knowledge of how different components of accruals map into future firm profitability and hence future stock returns. A benefit of these analyst revision tests is that, under the assumption that analyst forecasts are representative of the earnings expectations of the marginal investor, documenting systematic relations in sell-side analyst earnings expectations errors, makes it harder to attribute the negative relation between ΔNOA and future stock returns to a risk based explanation (e.g., Bradshaw, Richardson and Sloan, 2001, 2006).

All of the fundamental data used to compute the measures described in the following sub-section are derived from interim financial statements collected by Compustat. Analyst forecast data are sourced from I/B/E/S. Our market data are obtained from CRSP. Our tabulated analyses are based on winsorizing the top and bottom 1 percent of observations of variables (with the exception of stock returns and firm size) each month to minimize the influence of outliers. We include all firms in our analysis with non-missing data to compute measures of accruals and exclude financial firms (SIC between 6000 and 6999) as is standard in this literature.

2.2.1 Firm fundamentals

Our first empirical prediction can be stated in alternative form as:

P1: The negative relation between accruals and future firm profitability is stronger for the firm-specific component of accruals relative to the common component.

We test this by examining whether the negative relation between accruals, ΔNOA, and future firm profitability, ROA, differs across the components identified in section 2.1. We use a standard benchmark forecasting model for firm level profitability which acknowledges profitability is mean reverting and also exploits various firm characteristics that isolate differences in persistence of profitability (see e.g., Fama and French, 2000; and Hou, van Dijk and Zhang, 2012). Specifically, we run the following regression for each quarter (firm subscripts, i, dropped for the sake of brevity):

$$ROA_{t+1} =$$

$$\alpha + \beta_1 ROA_t + \beta_{2A} NOA_t^{FIRM} + \beta_{2B} NOA_t^{RELATED} + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 D\_Loss_t +$$

$$\beta_6 Div\_Yield_t + \beta_7 RET_t^{RELATED} + e_{t+1} \qquad (3)$$

ROA_t is return on assets for the previous twelve months, calculated as income before extraordinary items divided by average total assets. BTM_t is book-to-price measured as the book value of common equity divided by market capitalization using data available at the start of the period for which we examine future profitability, $Size_t$ is the log of market capitalization, D_Loss_t is an indicator variable equal to one for firms reporting a loss over the previous twelve months, and zero otherwise, Div_Yield_t is the dividend yield for the previous twelve months and $RET_t^{RELATED}$ is the average recent (6 month) stock returns of all related firms. We estimate this regression separately for each cross section and report Fama and Macbeth (1973) test statistics. In unreported tests, we have estimated equation (3) using a pooled sample clustering standard errors for both time and firm dependencies, and our results, if anything, are stronger.

We expect profitability to be mean reverting so our priors are for β_1 to be less than one and greater than zero. We expect firms with greater growth opportunities, as measured (inversely) by BTM_t , to have high levels of profitability after controlling for current profitability, so we expect a negative β_3 coefficient. We also expect smaller firms to exhibit higher levels of future profitability controlling for current profitability, so we expect a positive β_4 coefficient. We expect loss making firms to have lower profitability (i.e., $\beta_5 < 0$) and firms paying dividends to have higher profitability (i.e., $\beta_6 > 0$). We expect to find a strong unconditional relation between the performance of related firms along the supply chain (i.e., $\beta_7 > 0$). Finally, we expect a negative coefficient for our primary variable of interest, ΔNOA_t, but we expect this negative relation to be strongest for the firm specific component, ΔNOA_t^{FIRM}. We also further decompose our broad based measures of accruals into current and non-current components. Specifically, we compute ΔWC as the change in non-cash working capital and ΔNCO as the change in net non-current operating assets. Both measures are as defined in Richardson, Sloan, Soliman and Tuna (2005). We then re-estimate equation (3) allowing for separate regression coefficients across the 'firm specific' and 'related' components of these separate accrual measures. Our empirical predictions are similar: we expect the negative relation to be strongest for the 'firm specific' components. In our empirical tests we formally test for the difference in regression coefficients using standardized coefficients as this will capture any scale differences between the component measures of accruals.

2.2.2 Stock returns

Our empirical prediction can be stated in alternative form as:

P2: The negative relation between accruals and future stock returns is stronger for the firm-specific component of accruals relative to the common component.

We employ standard cross-sectional regressions and time series portfolio tests to assess the relation between future stock returns and ΔNOA across groups of firms formed on the basis of investment activity in related firms.

For our cross sectional tests, we run the following regression every month (again firm subscripts, *i*, dropped for the sake of brevity):

$$RET_{t+1} = \alpha + \beta_1 RET_t + \beta_2 \Delta NOA_t + \beta_3 BTM_t + \beta_4 {}^{NI}/_{P_t} + \beta_5 Beta_t + \beta_6 Size_t + \beta_7 Momentum_t + \beta_8 D\_Loss_t + \beta_9 RET_t^{RELATED} + e_{t+1} \qquad (4)$$

Equation (4) is estimated for the next month. In unreported tests, we have estimated equation (4) for the subsequent three months, results available upon request. The relevant test is whether $\beta_2 = 0$, and finding $\beta_2 < 0$ is consistent with stock returns failing to efficiently incorporate information about accruals in a timely manner. We are most interested in whether the magnitude of β_2 varies across the 'firm specific' and 'common' components of the various accrual measures. Consistent with prior research, we include firm characteristics known to be associated with future returns: NI/P_t and BTM_t (e.g., Fama and French, 1992 and 2008). BTM_t is as defined previously. NI/P_t is computed as net income before extraordinary items across the last four quarters divided by market capitalization as at the end of the most recent fiscal quarter. We expect both β_3 and β_4 to be positively associated with future returns. We also include measures of firm size, $Size_t$, as defined earlier, and $Beta_t$, measured as the single factor CAPM beta, using monthly data from the last 60 months for each security (minimum of 24 months required); we expect β_5 to be positive and β_6 to be negative. We also include two measures of recent stock returns. The first measure is RET_t, which is the return for the most recent month. Given prior research has documented a short term reversal effect (e.g., Jegadeesh, 1990) we expect β_1 to be negative. The second measure is $Momentum_t$, which is the most recent six month cumulative return dropping the most recent month. As prior research has shown a continuation in stock returns over the medium term, we expect β_7 to be positive. We also include an indicator for loss making firms, D_Loss_t, and $RET_t^{RELATED}$ as defined previously to capture the unconditional information content of related firm performance (we expect β_9 to be positive). We estimate equation (4) using value weighted cross sectional regressions. We use trailing twelve month financial statement data, and ensure that the data was publicly available by requiring a full three months from the fiscal quarter end before we use the data in our predictive analysis. For example, in April 2010 we will use financial statement data for the twelve month period ended December 31, 2009 for a December year end firm.

For our portfolio level analyses we sort firms into 25 groups. We first sort firms into five equal sized groups based on $\Delta NOA_t^{RELATED}$ and then within each group we sort firms into groups based on ΔNOA_t^{FIRM}. This allows us to assess the differential return performance of portfolios of firms formed on the basis of 'firm specific' components of accruals after having first sorted on 'common' components. The correlation between ΔNOA_t^{FIRM} and $\Delta NOA_t^{RELATED}$ is actually low (Pearson -0.09, Spearman -0.12), thus the ordering of the sorts does not affect our inferences. We examine both total returns and characteristic adjusted returns (Daniel, Grinblatt, Titman and Wermers, 1997) across the resulting portfolios. In addition we also report 'alphas' from time series regressions, where we regress portfolio monthly excess returns (over the return on the U.S. one-month Treasury bill) on (i) excess returns associated with market, MKT, (ii) factor mimicking portfolio returns associated with size, SMB, (iii) factor mimicking portfolio returns associated with book-to-price, HML, and (iv) factor mimicking portfolio returns associated with momentum, UMD. The factor returns for MKT, SMB, HML and UMD and the one-month Treasury return were obtained from Kenneth French's website at:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html.

2.2.3 Sell-side analyst earnings forecasts

Prior literature has shown that analyst forecasts appear to be slow in incorporating a variety of information (e.g., Bradshaw, Richardson and Sloan, 2001 and 2006 for measures of accruals and external financing). We revisit the strength of this relation based on the investment activity of related firms. Past research has used sell-side analyst earnings forecasts as proxies for earnings expectations of the marginal investor. Documenting systematic errors in earnings expectations with respect to a firm characteristic, such as accruals, which is associated with future stock returns, can be interpreted as prima facie evidence against a risk-based explanation. Our priors are that ΔNOA_t and its components, ΔNOA_t^{FIRM} and $\Delta NOA_t^{RELATED}$, should be systematically related to sell-side analyst earnings forecast revisions. Conditional on documenting a negative relation between ΔNOA_t (and its components) and future returns, we also expect to see a negative relation between sell-side analyst earnings revisions and ΔNOA_t (and its components). Therefore, our final empirical prediction can be stated in alternative form as:

P3: Sell-side analysts do not efficiently incorporate the differential negative relation between accrual components ('firm specific' and 'common') and future firm performance.

We test P3 directly by examining the speed with which analysts incorporate the information contained in ΔNOA_t into their firm level earnings forecasts. Specifically, we estimate the following regression every month (again firm subscripts, i, dropped for the sake of brevity):

$$Revision_{t+1} = \alpha + \beta_1 Revision_t + \beta_2 \Delta NOA_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + \beta_6 D\_Loss_t + \beta_7 RET_t^{RELATED} + e_{t+1} \quad (5)$$

Equation (5) is estimated for the next month. As with our stock return results, we have estimated equation (5) for the next three months, but for the sake of brevity we only report the first month. $Revision_t$ is the monthly revision in consensus sell-side analyst forecasts. To ensure cross-sectional comparability of sell-side analyst earnings forecasts across firms with different fiscal year ends, we first take a calendar weighted average of one year ahead, $E[EPS1Y_t]$, and two-year ahead earnings forecasts, $E[EPS2Y_t]$, where the weight is a linear function of the number of months to the end of the next fiscal year. We label the resulting twelve month ahead forecast: $E[EPS12M_t]$. For example, in March 2010 for a December year end firm we place 9/12 weight on the forecast for the 2010 fiscal year and 3/12 weight on the forecast for the 2011 fiscal year. The consequence of this choice is that our resulting earnings forecast is twelve months ahead for all firms. Finally, we compute $Revision_t$ as:

$$Revision_t = ln\frac{E[EPS12M_t]}{E[EPS12M_{t-1}]} \qquad (6)$$

Given that we use the natural logarithm operator we restrict our firms to those where the calendar weighted forecasts across both months are strictly positive, but our results are not sensitive to computing an alternative revision measure which retains negative forecasts. Prior literature has shown that analyst forecast revisions are highly serially correlated (e.g., Hughes, Liu and Su, 2008). We therefore expect β_1 to be positive. BTM_t and NI/P_t are as defined previously. We expect both β_3 and β_4 to be negative, as firms with high expectations of earnings growth should, on average, deliver that earnings growth (and changing expectations of growth). $Momentum_t$ is as defined previously. We include this variable as prior research has shown that sell side analyst forecasts reflect expectations embedded in stock price with a lag (e.g., Hughes, Liu and Su, 2008), and hence we expect β_5 to be positive. We also include an indicator for loss making firms, D_Loss_t, and $RET_t^{RELATED}$ as defined previously to capture the unconditional information content of related firm performance (we expect β_7 to be positive). Finally, we expect β_2 to be negative for our full sample estimation (Bradshaw, Richardson and Sloan, 2001), and we expect this negative relation to be greater for ΔNOA_t^{FIRM} relative to $\Delta NOA_t^{RELATED}$. As before, we estimate several variants of equation (5) examining the different components of accruals (i.e., ΔWC and ΔNCO).

3. Results

3.1 Firm fundamentals

Panel A of table 1 provides the breakdown of our sample firms across the industry groupings identified from the summary level BEA Surveys. For each industry we report distributional information of $\Delta NOA^{RELATED}$, our measure of investment activity in related firms. There are on average 125 industry groupings reflected in the summary level BEA data tables over the time period we examine, and for the sake of brevity we report this information only for the 30 most populated industry groupings. The 30 industry groupings we report in table 1 capture 68 percent of the total 766,496 firm-months that are in our full sample. We see considerable variation in the investment activity of related firms across each industry grouping *and* through time. This is a necessary condition for our research design to have any power. For example, over the 1988-2010 sample period, the related industries that do business with the computer and data processing service firms (Industry '73A' in the Table 1 panel A) experienced average annual growth in net operating assets equal to 7.03 percent of average assets. Further, this rate of growth in investment activity varied from 6.03 percent (lower quartile) to 8.74 percent (upper quartile) over these 23 years. In contrast, over the 1988-2010 sample period, the related industries that do business with software publishing firms (Industry '5112' in the Table 1 panel A) experienced average annual growth in net operating assets equal to -0.37 percent of average assets, with a lower (upper) quartile of -4.52 (2.45) percent. Clearly, there is considerable variation in the investment activities of related firms, and it is this variation we will exploit to examine the differential negative relation between sub-components of ΔNOA and future firm performance.

Panel B of table 1 reports distributional information for variables used in estimating regression equations (3), (4) and (5). The average firm in our sample has (i) monthly total returns of 1.3 percent, (ii) growth in net operating assets of 6.3 percent of average total assets, (iii) profitability of -4.6 percent of average total assets (limiting to profit only firms the average profitability is 7.6 percent of average total assets), (iv) a book-to-price ratio of 0.67, and (v) an earnings-to-price ratio of 0.04 (note that we compute this ratio only for profit firms). 36 percent of our sample firms report losses, and the dividend yield is 1.0 percent for the average firm. There is a considerable difference in the dispersion of the 'firm specific' and 'common' components of the accrual measures. For example, ΔNOA^{FIRM} has a pooled standard deviation of 0.243 and $\Delta NOA^{RELATED}$ has a pooled standard deviation of 0.051. We find similar differences in the relative scale of the 'firm specific' and 'common' components of the current and non-current measures of accruals. This is important for our statistical analysis. As we noted in section 2.2.1, we formally test for the difference in regression coefficients across 'firm specific' and 'common' components of accruals when estimating equations (3), (4) and (5) using standardized coefficients as this will capture any scale differences between the component measures of accruals. Failing to do this could erroneously reject the null hypothesis of equality of regression coefficients across 'firm specific' and 'common' components of accrual measures.

In unreported analysis, we have regressed ΔNOA onto a set of indicator variables capturing related industries at the summary level of the BEA input-output tables. The average adjusted R^2 from these monthly cross-sectional regressions (272 months in our sample) is 3.05%. Using alternative industry classification schema (e.g., Fama and French 1997 industry groupings) the adjusted R^2 can be increased to about 10 percent. This relatively low explanatory power suggests that only a small amount of the variation in accruals is attributable to common factors, a finding by itself that casts doubt on a risk based explanation for any negative relation between measures of accruals and future stock returns. In later empirical analysis (section 3.4.3) we also exploit time variation in the importance of $\Delta NOA^{RELATED}$ in explaining cross-sectional variation in ΔNOA to assess whether there is any evidence in support of the risk based explanation in time periods when related firm investment activity explains more of total investment activity.

Table 2 reports the standardized regression coefficient estimates of equation (3). We estimate this regression using 274,448 firm-quarter observations. We estimate equation (3) separately each cross-section and report Fama and Macbeth (1973) test statistics. There is no intercept in these regressions as we report standardized regression coefficients. In panel A we find results consistent with prior research: (i) profitability is mean reverting as evidenced by the β_1 coefficient of 0.686, (ii) the level of future profitability is increasing in $Size$, (iii) future profitability is lower (higher) for loss making (dividend paying) firms, and (iv) future profitability is positively related to the recent performance (as measured by stock returns) of related firms. All of these results are consistent with recent research (e.g., Hou, van Dijk and Zhang, 2012 and Menzly and Ozbas, 2010). We also find a strong negative relation between ΔNOA and future profitability, consistent with prior work on 'accruals' (e.g., Sloan, 1996, and Richardson, Sloan, Soliman and Tuna, 2005).

In panel B of table 2 we estimate equation (3) allowing for separate regression coefficients across the 'firm specific' and 'common' component of ΔNOA. Both components have a negative relation with future profitability, but the relation is stronger for ΔNOA_t^{FIRM} (a test statistic of -4.95 rejects the null hypothesis of equality across regression coefficients). In panel C we further decompose $\Delta NOA_t^{RELATED}$ into ΔNOA_t^{PEER} and $\Delta NOA_t^{NON-PEER}$ components as described in section 2.1 and Appendix I. Again we see negative coefficients for all components of ΔNOA, and consistent with P1 we see the strongest relation for the 'firm specific' component (test statistics reject the null hypothesis of equal coefficients).

In panel D of table 2 we estimate equation (3) allowing for separate regression coefficients for the current and non-current portion of ΔNOA. Consistent with Richardson, Sloan, Soliman and Tuna (2005), we see that both components have a negative relation with future firm profitability and that the relation is strongest for the current portion. Panels E and F of table 2 then allow for different regression coefficients for the 'firm specific' and 'common' components of ΔNOA. For the current portion of ΔNOA, we see that all of the negative relation is attributable to the 'firm specific' component (i.e., the regression coefficient on ΔWC_t^{FIRM} is strongly negative) and $\Delta WC_t^{RELATED}$, ΔWC_t^{PEER}, and $\Delta WC_t^{NON-PEER}$ are not related to future firm profitability. For the non-current portion of ΔNOA, see that the majority of the negative relation is attributable to the 'firm specific' component (i.e., the regression coefficient on ΔNCO_t^{FIRM} is strongly negative) and partly attributable to the 'common' component of peer firms (i.e., the regression coefficient on $\Delta NCO_t^{RELATED}$ is also negative, but it is significantly less negative than that for ΔNCO_t^{FIRM}).

Overall, the results in Table 2 suggest that the negative relation between broad based measures of accruals is strongest for the 'firm specific' component of accruals. This evidence is hard to reconcile with risk based explanations relying on time varying expected returns. Commonality in operating, investing and financing decisions as captured by common industry membership and supply chain linkages will be a primary determinant of risk and hence expected returns. If risk is the primary determinant of the negative relation between measures of accruals (i.e., investment) and future firm performance, then that relation should be strong when we focus on investment activity that is likely to be driven by common exposures to systematic risk.

Instead, we find that the negative relation between the 'common' component of measures of accruals and future firm performance is the weakest.

3.2 Stock returns

Table 3 reports our estimation of equation (4). We estimate this regression using 766,496 firm-month observations. As is standard in cross-sectional asset pricing tests we estimate this regression every month and use the time series of regression coefficients to construct test-statistics. Equation (4) is estimated for the next month. As with table 2, there is no intercept in these regressions as we report standardized regression coefficients. In panel A of table 3 we find, generally consistent with prior research, that future stock returns are (i) negatively correlated with the most recent stock returns, the 'reversal' effect, (ii) negatively associated with ΔNOA, (iii) positively associated with BTM and NI/P (albeit only significant for BTM), (iv) weakly positively associated with $Beta$, (v) negatively associated with $Size$, (vi) weakly negatively associated with $Momentum$ (our sample period finishes with the recent 'crash' associated with momentum, Daniel and Moskowitz, 2012), (vii) negatively associated with loss making status, and (viii) positively associated with the recent performance of related firms.

In panel B we estimate equation (4) allowing for separate regression coefficients across the 'firm specific' and 'common' component of ΔNOA. Both components have a negative relation with future returns, but the relation is far stronger for ΔNOA_t^{FIRM} (a test statistic of -5.58 rejects the null hypothesis of equality across regression coefficients, and the regression coefficient on $\Delta NOA_t^{RELATED}$ is marginally negative). In panel C we further decompose $\Delta NOA_t^{RELATED}$ into ΔNOA_t^{PEER} and $\Delta NOA_t^{NON-PEER}$ components. We continue to find that the majority of the negative relation between broad based measures of accruals and future stock returns is attributable to the 'firm specific' component of accruals (the regression coefficient on ΔNOA_t^{FIRM} is strongly different from zero and strongly different from both ΔNOA_t^{PEER} and $\Delta NOA_t^{NON-PEER}$).

Panels D, E and F then allow for an additive decomposition of ΔNOA into its current and non-current components. In panel F we only report regression coefficients on components of ΔNOA to ensure the table is readable. Consistent with Richardson, Sloan, Soliman and Tuna (2005), we see that both components have a negative relation with future stock returns. For both the current and non-current portions of ΔNOA, see that the negative relation is entirely attributable to the 'firm specific' component (i.e., the regression coefficients on both ΔWC_t^{FIRM} and ΔNCO_t^{FIRM} are strongly negative, and the regression coefficients on $\Delta WC_t^{RELATED}$ and $\Delta NCO_t^{RELATED}$ are not reliably negative). Furthermore, formal tests of difference across the components strongly reject the null hypothesis of equality of regression coefficients. Overall, the results in Table 3 suggest that the negative relation between broad based measures of accruals is strongest for the 'firm specific' component of accruals. As discussed earlier, this evidence is hard to reconcile with risk based explanations for the negative relation between measures of accruals and future stock returns.

To visualize the significance of the difference in the strength of the negative relation between components of ΔNOA and future stock returns, we sort firms into quintiles each month based on ΔNOA and its components (i.e., ΔNOA^{FIRM} and $\Delta NOA^{RELATED}$) over the most recent four fiscal quarters. We then compute a hedge portfolio return as the difference between the long return for the lowest quintile of ΔNOA (or the relevant component) and the short return for the highest quintile of ΔNOA (or the relevant component) and cumulate these monthly portfolio returns. The cumulated portfolio returns are shown in Figure 1. The bold line plots these cumulative portfolio returns based on ΔNOA. The long (short) dashed line plots these cumulative portfolio returns based on ΔNOA^{FIRM} ($\Delta NOA^{RELATED}$). It is clear that the vast majority of the negative relation between measures of accruals and future stock returns is attributable to the 'firm specific' component. To test the relative attractiveness of the portfolio returns for the components of ΔNOA, we conduct standard asset pricing tests to determine optimal portfolio weights in a mean-variance framework (e.g., Britten-Jones, 1999). This test simply regresses a vector of 1s against the time series of the relevant asset (i.e., portfolio) returns and the coefficients from the regression provide the optimal in-sample weight to achieve the best (i.e., closest to an arbitrage opportunity) returns for an investor. This test reveals that the optimal weight is to 'long' the ΔNOA^{FIRM} portfolio and 'short' the $\Delta NOA^{RELATED}$ portfolio, confirming that the negative relation between measures of accruals and future stock returns is attributable to the 'firm specific' component. Inferences are virtually identical if we use characteristic adjusted returns (e.g., Daniel, Grinblatt, Titman and Wermers, 1997) instead of total returns when computing the portfolio returns.

To help assess the robustness of the results to the linearity assumption underlying our regression analysis reported in table 3, we also document the relation across portfolios formed on the joint sort of $\Delta NOA^{RELATED}$ and ΔNOA^{FIRM}. Specifically, each month we first sort all firms into five equal sized groups based on investment activity in related firms (i.e., $\Delta NOA^{RELATED}$) and then within each $\Delta NOA^{RELATED}$ quintile, we further sort firms into five equal sized groups based on firm specific accruals (i.e., ΔNOA^{FIRM}). As described in section 2.2.2, the correlation between $\Delta NOA^{RELATED}$ and ΔNOA^{FIRM} is low so the ordering of sorts does not affect our inferences in the portfolio analysis.

Panel A (B) of table 4 reports the total (characteristic-adjusted) monthly return across the 25 cells. We see strong evidence of the negative relation between ΔNOA^{FIRM} and future stock returns: there is a strong negative 'HI-LO' return for each column in both panels A and B. In contrast, the 'HI-LO' return spread across rows is only significantly negative in the bottom row of panel A. It is worth noting that the spread in ΔNOA across rows is less than the spread in ΔNOA down columns. Part of the weaker negative relation between $\Delta NOA^{RELATED}$ and future stock returns could be attributable to the lower spread in ΔNOA. However, as noted previously, our statistical tests in table 3 allow for differences in scale of the components of ΔNOA. Finally, in panel C of table 4 we report the intercepts from time-series regressions where we regress portfolio monthly excess returns (over the return on the U.S. one-month Treasury bill) on (i) excess returns associated with market, MKT, (ii) factor mimicking portfolio returns associated with size, SMB, (iii) factor mimicking portfolio returns associated with book-to-price, HML, and (iv) factor mimicking portfolio returns associated with momentum, UMD. We again see a significant negative relation between ΔNOA^{FIRM} and future 'alphas', but not a significant negative relation between $\Delta NOA^{RELATED}$ and future 'alphas'.

Across the analyses reported in tables 3 and 4, we find evidence consistent with P2 that the negative relation between accruals and future stock returns is stronger for the firm-specific component of accruals relative to the common component. Of course, this inference is conditional on our ability to appropriately measure expected returns (e.g., Fama, 1998). However, a benefit of additively decomposing ΔNOA into a 'firm specific' and 'common' component is that the negative relation between investment activity and future stock returns is expected to be strongest for 'common' component where management are more likely to be basing their investment decisions on time varying expected returns. We do not see strong evidence in support of this risk based explanation for the negative relation.

3.3 Analyst revisions

Table 5 reports our estimation of regression equation (5). For this analysis we have a smaller sample due to the requirement of sell-side earnings forecasts collated by I/B/E/S. Our full sample comprises 344,624 firm-months, with equation (5) estimated each month, regression coefficients averaged across months, and standard errors based on the time series variation in the monthly regression coefficients. As with tables 2 and 3, there is no intercept in these regressions as we report standardized regression coefficients. In panel A we see that analyst revisions are (i) serially correlated, (ii) positively related to market expectations for growth (the β_3 and β_4 coefficients are significantly negative, but the measures are 'yields'), (iii) strongly related to past returns (the β_5 coefficient is significant for the following three months), (iv) positively associated with past loss making occurrence suggesting that analysts are initially too pessimistic for loss making firms, and (v) positively associated with recent performance of related firms (the β_7 coefficient is strongly positive consistent with Menzly and Ozbas, 2010). Finally, consistent with Bradshaw, Richardson and Sloan (2001) we find a robust negative relation between ΔNOA and future analyst revisions, consistent with analyst failing to incorporate the information content of broad based measures of accruals in a timely manner. Given the strong negative relation between ΔNOA and future returns, the systematic error in earnings expectations of analysts is prima facie evidence against a risk based explanation (see also Bradshaw, Richardson and Sloan, 2001).

In panel B we estimate equation (5) allowing for separate regression coefficients across the 'firm specific' and 'common' component of ΔNOA. Both components have a negative relation with future analyst revisions, but the relation is only significant for ΔNOA_t^{FIRM} (and a test statistic of -4.82 rejects the null hypothesis of equality across regression coefficients). In panel C we further decompose $\Delta NOA_t^{RELATED}$ into ΔNOA_t^{PEER} and $\Delta NOA_t^{NON-PEER}$ components. We continue to find that the negative relation between broad based measures of accruals and future stock returns is attributable to the 'firm specific' component of accruals (the regression coefficient on ΔNOA_t^{FIRM} is strongly different from zero and strongly different from both ΔNOA_t^{PEER} and $\Delta NOA_t^{NON-PEER}$). As discussed in section 2.3.3, conditional on finding a stronger relation between ΔNOA_t^{FIRM} and future stock returns, the mispricing explanation for this relation suggests a stronger relation between systematic errors in analyst earnings expectations and ΔNOA_t^{FIRM}. The results are consistent with a mispricing and not a risk-based explanation for the negative relation between measures of accruals and future firm performance.

Panels D, E and F then allow for an additive decomposition of ΔNOA into its current and non-current components. In panel F we only report regression coefficients on components of ΔNOA to ensure the table is readable. In panel D we see that both the current and non-current portions of ΔNOA have a reliably negative association with future analyst revisions confirming past research that analysts are slow in incorporating information about current and non-current accruals. In panel E we see that the negative relation is <u>entirely</u> attributable to the 'firm specific' component (i.e., the regression coefficients on both ΔWC_t^{FIRM} and ΔNCO_t^{FIRM} are strongly negative, and the regression coefficients on $\Delta WC_t^{RELATED}$ and $\Delta NCO_t^{RELATED}$ are not reliably negative). Furthermore, formal tests of differences across the components strongly reject the null hypothesis of equality of regression coefficients. Overall, the results in table 5 are consistent with P3 that sell-side analysts do not efficiently incorporate information on investment decisions of firms into their earnings forecasts, and that this relation is almost entirely attributable to the 'firm specific' component of accruals. As noted earlier, a benefit of the analyst revision tests is that, under the assumption that analyst earnings forecasts are representative of the earnings expectations of the marginal investor, documenting systematic relations in sell-side analyst earnings expectations errors, suggests that the relation between ΔNOA and future stock returns is attributable to errors in expectations on future cash flows and not attributable to a risk based explanation.

3.4 Extensions

3.4.1 Rescaling USE and MAKE tables to allow scale for each industry to sum to less than one

Our empirical analysis is based on several choices in converting the MAKE and USE tables of the BEA into an industry level input-output table. One of the choices that we made was to force both the MAKE and USE table to have rows sum to one (i.e., we forced the total commodity production for each industry to sum to 100 percent, *and* we forced the total commodity usage for each industry to sum to 100 percent). The BEA MAKE and USE tables include government and related categories which we do not consider in our analysis (such categories do not contain firms). However, this choice could lead to inconsistent treatment in the economic importance in the links across industries. For example, a given commodity may ultimately be primarily used by the government and our choice to force the usage to sum to 100 percent could artificially increase the scale of input-output links for government facing industries. To address this issue we have instead allowed the rows of the MAKE and USE table to sum to less than 100 percent and thereby preserve the natural scale of the economic importance across industries. Our results are virtually identical from this analysis (for the sake of brevity, these results available on request).

3.4.2 Variation in investment cycle and lead-lag relations

Our empirical analysis has identified that the negative relation between broad based measures of accruals and future firm performance is attributable to the 'firm specific' component of accruals and is largely absent for the 'common' component of accruals. This absence of a relation for the 'common' component of accruals is difficult to reconcile with the 'q theory' where managers dynamically change their investment decisions in response to time variation in expected returns.

Investment activity, however, is often 'long tailed' where it may take more than one fiscal year for investment activity to be realized in response to time variation of expected returns. As a consequence, we may find an absence of a negative relation between the 'common' component of investment activity and future stock returns because the 'firm specific' component responds with a lag to the 'common' component. We offer two supplemental arguments in response to this. First, we have decomposed the broad based measure of investment activity into current (i.e., ΔWC) and non-current (i.e., ΔCOA) components. We agree that investment activity is expected to respond slowly to changes in expected returns, but we also expect that the 'speed' of reaction would be slower for the non-current component of accruals relative to the current component of accruals. Our results suggest that the strength of the negative relation between 'firm specific' component is at least as strong for the current portion as it is for the non-current portion, suggesting that differential investment cycles is unlikely to explain our results. Second, we have explicitly added lagged values of the 'common' component of investment activity to our regression specifications. The lagged values of the common component of accruals are marginally negative significant in regression equation (3) and not significant in regression equations (4) or (5). But more importantly the main result that the negative relation between the 'firm specific' component of accruals and future firm performance is stronger than the negative relation between the 'common' component of accruals and future firm performance remains.

3.4.3 Variation in the importance of related firm investment activity and lead-lag relations

A central tenet of the 'q-theory' to explain the negative relation between broad based measures of accruals and future firm performance is managers rationally respond to common variation in expected returns. Our empirical analysis to date is difficult to reconcile with this interpretation. However, as noted in section 3.1, unconditionally the accrual activity of related firms explains only a small fraction of total accrual activity. To help increase the power of tests to support the 'q theory' we can also measure time series variation in the explanatory power of related firms for total accrual activity. It is possible that the relation between related firm accrual activity and future firm performance is limited to time periods when related firm accrual activity explains a greater portion of total accrual activity.

We test this alternative explanation as follows. First, each month we regress ΔNOA onto a set of industry indicator variables capturing related firms and compute the adjusted R^2 from this regression. We then average these adjusted R^2 over the previous one to six months. Second, we extract the Fama-Macbeth regression coefficients for ΔNOA^{FIRM} and $\Delta NOA^{RELATED}$ when estimating equation (4) each month. We then average these regression coefficients over the following one to six months. If time series variation in the importance of related firm accrual activity is important in affecting the negative relation between broad measures of accruals and future performance, we should see a negative relation between the lagged adjusted R^2 and leading measures of the predictive ability of accrual components as described above (i.e., as related firm investment activity becomes more important, then $\Delta NOA^{RELATED}$, and not ΔNOA^{FIRM}, should become more negatively associated with future stock returns). We find that the negative relation is indeed greater, but the effect is strongest for the firm specific portion of accruals and only moderately significant for the related firm component of accruals. Again, this result is hard to reconcile with the 'q theory'.

3.4.4 Alternative risk based explanations

Our empirical analysis has focused on the 'q theory' explanation for the observed negative association between broad based measures of accruals and future firm performance. There are alternative risk based explanations which entertain factors other than industry as possible sources of systematic risk. One approach that has been used in prior literature is to isolate whether it is the accrual characteristic rather than an accrual factor loading that predicts returns. This approach was introduced in Daniel and Titman (1997) and was used in the context of accruals in Hirshleifer, Hou and Teoh (2012). A key feature of this approach is seeking to document whether, and how, stock returns co-move more strongly for firms that share a similar characteristic.

To assess the possibility that portfolios formed on the basis of accruals exhibit greater co-movement, we explore the correlation structure of stock returns within and across accrual portfolios. Specifically, each month we sort the full cross-section into ten equal sized groups based on ΔNOA and compute (i) the average pairwise correlation across all constituents in each accrual portfolio, and (ii) the average pairwise correlation across constituents in a given accrual portfolio with constituents in other accrual portfolios. We use monthly returns for the next 12 months to compute each pairwise correlation. We repeat this procedure every month (272 months in our sample) and compute the global average of average pairwise correlations of stock returns across the various accrual portfolios. This procedure results in 100 average pairwise correlations across the ten accrual portfolios. If risk is a valid explanation for the observed negative relation between measures of accruals and future returns, then we should see a higher pairwise correlations within the low accrual portfolio (higher future returns) relative to the high accrual portfolio (lower future returns), and that there should be higher (lower) pairwise correlations across stocks in the low (high) accrual portfolio and stocks in other portfolios. We find that the average pairwise correlation for common stocks within the low (high) accrual portfolio is 0.103 (0.129). We further find that the average pairwise correlation for low (high) accrual stocks and all other stocks to be 0.105 (0.120). To measure the significance of these differences in correlations we repeat our sorting process 100 times by randomly assigning stocks to ten portfolios. The boot-strapped confidence interval of average pairwise correlations for the randomly assigned portfolios is between 0.114 - 0.118. Thus, we find evidence that the average pairwise correlation for the low (high) accrual portfolio is lower (higher) both within and across accrual portfolios. Table 6 reports the 100 average pairwise stock return correlations. For ease of interpretation, we have shaded the cells to reflect the strength of the return correlations: lighter (darker) shading reflects weaker (stronger) correlations. These results are difficult to attribute to a risk based explanation for the negative relation between measures of accruals and future stock returns: stocks with low (high) levels of accruals behave in a less (more) systematic manner than stocks with high (low) levels of accruals, yet they deliver higher (lower) future stock returns.

4. Conclusion

In this paper we examine whether risk based explanations for the negative relation between broad based measures of accruals and future firm performance are consistent with the data. 'Q theory' notes that managers are able to observe time variation in expected returns and rationally respond by changing investment decisions through time. As researchers we observe these investment decisions ex post. Under the assumption of rational manager behaviour and time varying expected returns, any observed negative relation between investment activity (e.g., measures of accruals) and future firm performance is attributable to risk. We agree that this assertion of a risk based explanation for the 'accrual anomaly' has merit. However, the assertion by itself is relatively empty as it does not allow for empirical falsification.

We extend the risk based explanation under a very general argument that exposure to systematic risk is the primary determinant of expected returns. In turn, a primary determinant of exposure to systematic risk is commonality in operating, investing and financing decisions. Such decisions are likely to be shared by firms operating in similar business environments. We measure this by identifying firms into economically related groups based on common industry membership and shared industry level supply chains. We then additively decompose various measures of accruals into 'firm specific' and 'common' components.

We show that the well-known negative relation between accruals and future firm performance is primarily attributable to the firm specific component. We argue that this result is hard to reconcile to the risk based explanation for the observed negative relation between accruals and future firm performance. This is because, whatever the source and price of risk, it is likely to be shared by firms operating in similar environments. We are unable to document a reliably negative relation between observed investment activity and stock returns along this ‘common’ dimension. However, there is a very strong negative relation for the ‘firm specific’ component suggesting that risk cannot be a complete explanation for the ‘accrual anomaly’.

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Appendix I: Bureau of Economic Analysis Survey Tables

We use the Benchmark Input-Output Surveys of the Bureau of Economic Analysis (BEA Surveys) as the basis for identification of economically linked industries. These data allow us to cleanly identify linkages across customer and supplier industries. The BEA surveys provide a detailed view into the interdependencies across industries based on the production and consumption of various goods and services. The BEA Surveys are updated every 5 years and are dated with a 'look-back', and we are careful to ensure that we use this data when it was publicly available. For example, the tables identified as '2002' were released in September 2007 to cover the industry output over the 2002-2007 period. We only use this data after the public release of the '2002' table during the 2007 calendar year.

The BEA Surveys contain a variety of tabulated information. We are most interested in the MAKE and USE tables. The MAKE table is a $I \times C$ matrix populated with the dollar production of each commodity, c, by each industry, i. Thus, the sum of the cells in each row (industry) of the MAKE table reflects the total production of commodities for that industry. The USE table is a $C \times I$ matrix populated with the dollar consumption of each commodity, c, by each industry, i. Thus, the sum of the cells in each row of the USE table reflects the total consumption of a given commodity across all industries.

We need to make several research design choices when using the BEA Surveys. First, we need to decide on the granularity of industry definition. The BEA Surveys are provided at a detailed, summary and sector level. For the 2002 BEA Surveys the dimensionality of the MAKE and USE tables across these three levels are as follows: (i) detailed (430 industry codes), (ii) summary (133 industry codes), and (iii) sector (15 industry codes). We use the summary level BEA Surveys in our empirical analysis. Second, we need to combine some intermediary industry codes to allow mapping back to standard industry classification schema such as SIC and GICS. These are performed manually for a small number of industry codes (see Menzly and Ozbas, 2010 for details). Third, we need to combine the MAKE and USE tables to create a balanced *I x I* matrix reflecting the *proportional* use of commodities that are produced and then used across industries within the US economy. To do this we convert the MAKE table to reflect the proportion of a given commodity that is produced by a given industry. The dollar amounts in the cells of the *I x C* MAKE table are therefore scaled by the respective sum of each row (i.e., the total amount of a given commodity that is produced by a given industry, relative to the total amount of commodities produced by that industry). Likewise, we convert the USE table to reflect the proportion of a given commodity that is consumed by a given industry. The dollar amounts in the cells of the *C x I* USE table are therefore scaled by the respective sum of each row (i.e., the total amount of a given commodity that is consumed by a given industry, relative to the total amount of that commodity that is consumed across all industries in the US economy). We then take the matrix multiplication across the modified MAKE and USE tables to create an *I x I* industry level input-output table.

Appendix II shows the final input-output table for the sector level (15 industry codes) using the 2002 BEA Survey tables. For example, the agriculture, forestry, fishing and hunting sector (labelled as AGRIC) consumes 31 percent of the commodities that it produces and the bulk of the rest is consumed by the manufacturing sector (labelled as MANUF). It is clear from this visualization that there is a concentration of economic activity along the main diagonal. Thus, our input-output matrix reflects the combined effect of related firms in the same industry and related firms that operate in different industries. Not surprisingly, there is a strong within industry economic interdependence between firms in the US economy. In our empirical analysis we separately examine the two types of related firms. ‘Peer’ firms are those in the same industry grouping (i.e., diagonal elements of the input-output table), and ‘non-peer’ firms are those along the supply chain (i.e., non-diagonal elements of the input-output table).

Appendix II: Visualization of the 2002 Sector level input-output table

PRODUCERS \ USERS	AGRIC.	MINES	UTIL	CONSTR	MANUF	WSALE	RETAIL	TRANS	INFO	FIN	BUS SRVC	SOCIAL	ARTS	OTH SRVC	GOVT
AGRIC	0.310	0.002	0.000	0.012	0.627	0.001	0.008	0.000	0.000	0.007	0.004	0.002	0.018	0.001	0.008
MINES	0.004	0.035	0.243	0.042	0.600	0.002	0.003	0.007	0.003	0.008	0.004	0.005	0.004	0.002	0.038
UTIL	0.029	0.025	0.002	0.020	0.321	0.025	0.066	0.020	0.023	0.097	0.043	0.082	0.077	0.025	0.144
CONSTR	0.008	0.043	0.047	0.004	0.080	0.007	0.020	0.029	0.035	0.364	0.033	0.017	0.018	0.017	0.277
MANUF	0.017	0.007	0.004	0.096	0.551	0.018	0.026	0.027	0.023	0.025	0.030	0.047	0.032	0.015	0.084
WSALE	0.026	0.007	0.004	0.071	0.483	0.072	0.040	0.023	0.020	0.043	0.029	0.051	0.035	0.016	0.080
RETAIL	0.004	0.005	0.002	0.507	0.116	0.014	0.032	0.030	0.009	0.115	0.027	0.034	0.028	0.056	0.021
TRANS	0.018	0.010	0.059	0.044	0.233	0.075	0.076	0.181	0.033	0.039	0.063	0.028	0.021	0.019	0.101
INFO	0.001	0.004	0.004	0.027	0.107	0.029	0.034	0.020	0.291	0.085	0.143	0.053	0.027	0.025	0.151
FIN	0.019	0.015	0.006	0.022	0.058	0.028	0.060	0.031	0.033	0.422	0.094	0.089	0.035	0.046	0.042
BUS SRVC	0.002	0.012	0.008	0.046	0.204	0.054	0.049	0.031	0.061	0.112	0.153	0.067	0.043	0.023	0.134
SOCIAL	0.022	0.000	0.003	0.005	0.004	0.010	0.044	0.002	0.010	0.005	0.013	0.451	0.010	0.037	0.384
ARTS	0.002	0.002	0.020	0.022	0.090	0.024	0.030	0.028	0.101	0.133	0.217	0.073	0.101	0.034	0.123
OTH SRVC	0.007	0.002	0.004	0.091	0.119	0.040	0.044	0.034	0.048	0.163	0.130	0.077	0.048	0.036	0.156
GOVT	0.004	0.002	0.005	0.004	0.046	0.085	0.085	0.149	0.047	0.088	0.080	0.126	0.091	0.033	0.155

Appendix II: The final input-output table for the sector level (15 industry codes) using the 2002 Bureau of Economic Analysis Survey tables. To create this sector level input-output table we first transform the respective *MAKE* and *USE* tables to create a balanced matrix reflecting how the total set of commodities are produced and utilized across the US economy. Details can be found in section 2.1 and Appendix I. The shading of cells reflects the strength of the industry level input-output linkages, with the darker cells reflecting stronger linkages.

Appendix III: Variable definitions

Variable	Description
$Beta$	Equity market beta estimated from a rolling regression of 60 months of data requiring at least 24 months of non-missing return data.
BTM	Book-to-market ratio computed as the ratio of common equity to equity market capitalization, both measured at the fiscal period end date for the most recent *and* available fiscal quarter prior to month *t*.
Div_Yield	Dividends per share over the previous twelve months divided by the stock price.
D_Loss	An indicator variable equal to one for firms that have negative earnings before extraordinary items over the previous twelve months and zero otherwise.
ΔNOA	The change of net operating assets over the previous twelve months, scaled by average total assets, where net operating assets are calculated as operating assets (total assets less the sum of cash and investments) minus operating liabilities (total liability minus total debt).
ΔWC	The change of working capital accruals over the previous twelve months, scaled by average total assets, where working capital accruals are calculated as current operating assets (current assets less cash and short term investments) minus current operating liabilities (current liabilities less debt in current liabilities).
ΔNCO	The change of non-current operating assets (total assets less current assets less investments and advances) less non-current operating liabilities (total liabilities less current liabilities less long-term debt) over the previous twelve months, scaled by average total assets.
$\Delta NOA^{RELATED}$	The average change of net operating assets in the related firms over the previous twelve months, scaled by average total assets. Related firms include those firms in the same industry grouping ($PEERS$) as well as firms in industries linked via the Bureau of Economic Analysis Input-Output tables ($NON-PEERS$).
ΔNOA^{PEERS}	The average change of net operating assets in the related $PEER$ firms over the previous twelve months, scaled by average total assets.
$\Delta NOA^{NON-PEERS}$	The average change of net operating assets in the related $NON-PEER$ firms over the previous twelve months, scaled by average total assets.
$\Delta WC^{RELATED}$	The average change of working capital accruals in the related firms over the previous twelve months, scaled by average total assets. Related firms include those firms in the same industry grouping ($PEERS$) as well as firms in industries linked via the Bureau of Economic Analysis Input-Output tables ($NON-PEERS$).
ΔWC^{PEERS}	The average change of working capital accruals in the related $PEER$ firms over the previous twelve months, scaled by average total assets.
$\Delta WC^{NON-PEERS}$	The average change of working capital accruals in the related $NON-PEER$ firms over the previous twelve months, scaled by average total assets.
$\Delta NCO^{RELATED}$	The average change of non-current operating assets less non-current operating liabilities in the related firms over the previous twelve months, scaled by average total assets. Related firms include those firms in the same industry grouping ($PEERS$) as well as firms in industries linked via the Bureau of Economic Analysis Input-Output tables ($NON-PEERS$).
ΔNCO^{PEERS}	The average change of non-current operating assets less non-current operating liabilities in the related $PEER$ firms over the previous twelve months, scaled by average total assets.

$\Delta NCO^{NON-PEER}$	The average change of non-current operating assets less non-current operating liabilities in the related $NON-PEER$ firms over the previous twelve months, scaled by average total assets.
ΔNOA^{FIRM}	The difference between ΔNOA and $\Delta NOA^{RELATED}$.
ΔWC^{FIRM}	The difference between ΔWC and $\Delta WC^{RELATED}$.
ΔNCO^{FIRM}	The difference between ΔNCO and $\Delta NCO^{RELATED}$.
HML	Monthly return to the value factor, obtained from Ken French's website.
MKT	Monthly excess (to risk free rate) market return, obtained from Ken French's website.
MOM	Monthly return to the momentum factor, obtained from Ken French's website.
$Momentum$	The average monthly equity return inclusive of dividends from month *t-6* to month *t-1*.
NI/P	Earnings-to-Price ratio computed (i) for positive income firms as the ratio of net income before extraordinary items for the previous twelve months to equity market capitalization, both measured at the fiscal period end date for the most recent *and* available fiscal quarter prior to month *t*, and (ii) for loss firm it is set equal to zero.
RET	Monthly equity return inclusive of dividends.
$RET^{RELATED}$	The average value weighted monthly equity return inclusive of dividends from month *t-6* to month *t* of the related firms.
ROA	Return on assets computed as the ratio of net income before extraordinary items for the previous twelve months to average total assets.
$Revision$	This is the monthly revision in median consensus sell-side analyst earnings forecasts. Earnings forecast revision is calculated as $Revision_{i,t+k} = \ln\frac{E[EPS12M_{i,t+k}]}{E[EPS12M_{i,t+k-1}]}$, where $E[EPS12M_{i,t}]$ is a calendar weighted combination of one year ahead, $E[EPS1_{i,t}]$, and two year ahead, $E[EPS2_{i,t}]$, earnings forecasts as at month *t*. The weights across the two earnings forecasts are chosen such that the combined forecast is for twelve months ahead. This ensures cross-sectional comparability across earnings forecast revisions.
$Size$	Natural logarithm of equity market capitalization.
SMB	Monthly return to the size factor, obtained from Ken French's website.

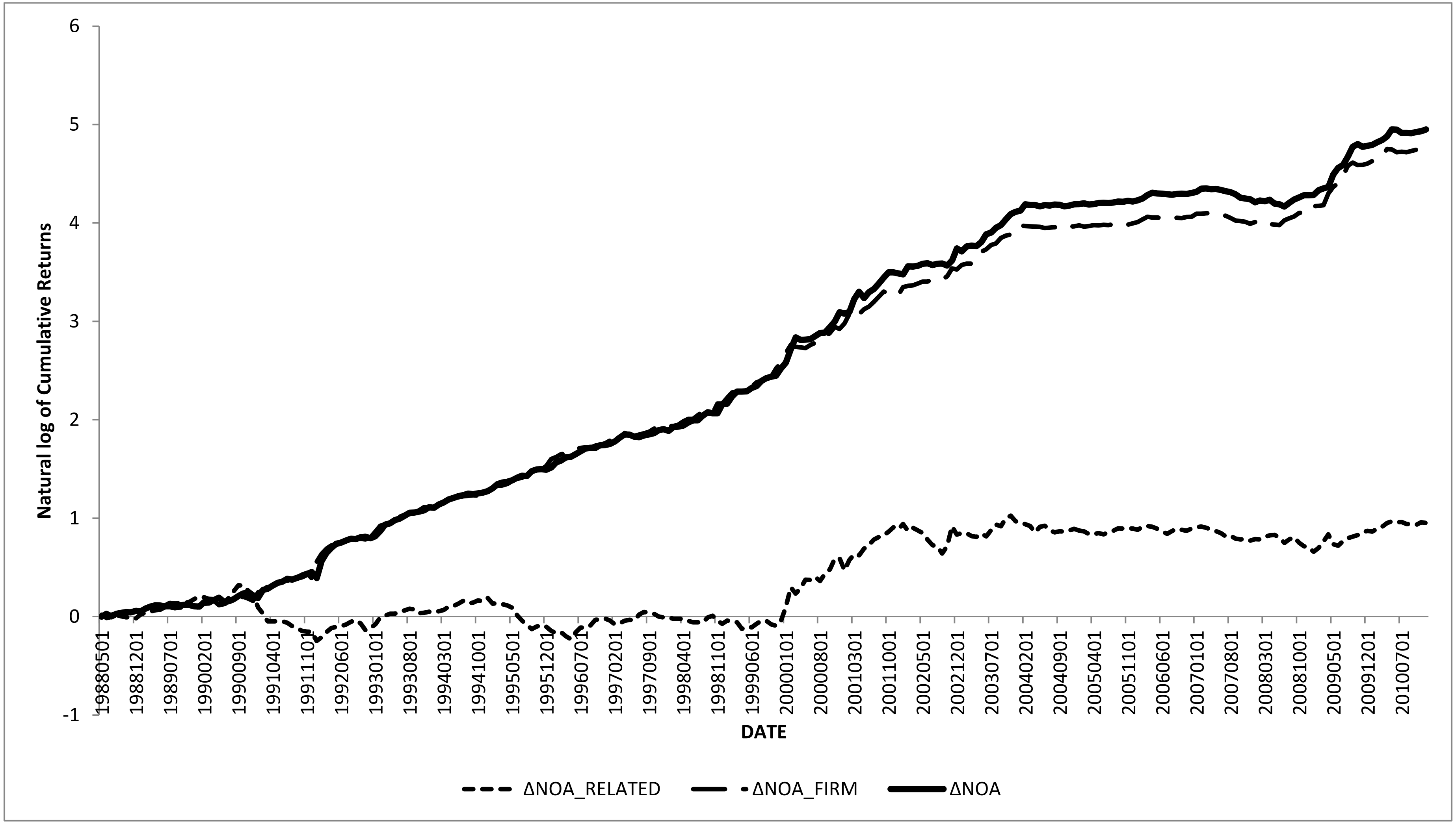

Figure 1: Cumulative Returns of ΔNOA. Each month firms are sorted into five equal sized portfolios based on the growth in net operating assets (ΔNOA) as shown by the bold line. Each month firms are also sorted into five equal sized groups based on NOA^{FIRM} (long dashed line) and $NOA^{RELATED}$ (short dashed line). $NOA^{RELATED}$ is the value weighted average of all firms economically related to that firm (e.g., shared industry membership), and NOA^{FIRM} is the difference between ΔNOA and $NOA^{RELATED}$.

Table 1
Sample Details

Panel A: Distribution of investment activity of the related firms across industry groupings ($\Delta NOA^{RELATED}\ \%$)

Industry	Firm/month Obs.	$\Delta NOA^{RELATED}$ Mean	Std. Dev.	Q1	Q3
73A Computer and data processing services	48679	7.03	2.51	6.03	8.74
62 Scientific and controlling instruments	39235	7.44	4.33	3.34	11.27
69B Retail trade	36360	8.90	4.12	6.29	11.27
29A Drugs	31310	8.14	5.08	4.30	9.69
3254 Pharmaceutical and medicine manufacturing	30054	3.37	2.39	1.31	5.15
69A Wholesale trade	28037	5.40	2.44	3.12	7.28
4A00 Retail trade	21462	0.71	2.99	-0.78	2.69
51 Computer and office equipment	19863	6.50	3.34	3.71	8.61
73C Other business and professional services, except medical	19455	6.80	2.76	5.22	8.80
56 Audio, video, and communication equipment	18079	7.34	4.96	2.48	11.24
5112 Software publishers	17618	-0.37	4.71	-4.52	2.45
57 Electronic components and accessories	17483	6.68	3.69	2.74	9.14
3344 Semiconductor and electronic component manufacturing	16961	0.76	3.83	-2.33	3.40
3345 Electronic instrument manufacturing	16926	0.95	3.78	-1.36	3.11
08 Crude petroleum and natural gas	13746	4.08	3.22	1.62	5.62
77A Health services	13298	10.77	8.04	4.31	14.22
4200 Wholesale trade	13248	1.40	3.22	-0.50	3.28
66 Communications, except radio and TV	13124	7.12	4.28	3.52	10.13
74 Eating and drinking places	11620	5.92	2.15	4.61	7.34
68A Electric services (utilities)	10893	5.03	2.36	2.78	6.79
5415 Computer systems design and related services	10153	1.74	2.39	0.48	3.39
334AAudio, video, and communications equipment manufacturing	10022	-0.37	4.09	-4.71	2.91
2110 Oil and gas extraction	9734	5.04	3.65	2.72	6.27
3341 Computer and peripheral equipment manufacturing	9235	0.03	3.51	-3.33	2.81
3391 Medical equipment and supplies manufacturing	8928	3.98	2.53	2.82	5.74
32 Rubber and miscellaneous plastics products	7934	5.91	2.96	3.23	8.02
11+12 Construction	7570	5.33	2.41	3.47	7.05
2211 Power generation and supply	6880	1.78	3.28	0.09	4.51
68B Gas production and distribution (utilities)	6595	4.70	2.45	2.55	6.43
7220 Food services and drinking places	6540	2.17	2.44	0.42	3.96

Panel B: Firm characteristics (N=766,496 firm-months)

Variable	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
RET	0.013	0.208	-0.927	-0.082	0.000	0.082	24.00
ΔNOA	0.063	0.246	-0.560	-0.036	0.037	0.139	0.880
ΔNOA^{FIRM}	0.013	0.243	-0.610	-0.087	-0.008	0.090	0.819
$\Delta NOA^{RELATED}$	0.050	0.051	-0.076	0.021	0.050	0.077	0.189
ΔWC	0.012	0.114	-0.308	-0.027	0.007	0.050	0.347
ΔWC^{FIRM}	0.008	0.113	-0.314	-0.031	0.004	0.045	0.338
$\Delta WC^{RELATED}$	0.004	0.014	-0.038	-0.002	0.004	0.012	0.042
ΔNCO	0.051	0.206	-0.444	-0.021	0.019	0.089	0.802
ΔNCO^{FIRM}	0.004	0.205	-0.492	-0.074	-0.020	0.048	0.738
$\Delta NCO^{RELATED}$	0.047	0.048	-0.062	0.020	0.041	0.071	0.173
NI/P	0.044	0.124	0	0	0.032	0.065	0.237
BTM	0.669	0.719	0.034	0.286	0.504	0.821	3.241
ROA	-0.046	0.298	-1.166	-0.053	0.029	0.073	0.272
$SIZE$	11.966	2.162	7.552	10.395	11.861	13.441	17.221
$Momentum$	0.013	0.088	-0.189	-0.029	0.009	0.048	0.294
$Revision$	0.012	0.396	-0.595	0	0.014	0.032	0.536
$BETA$	1.163	0.881	-0.596	0.601	1.056	1.583	3.969
D_Loss	0.355	0.478	0	0	0	1	1
Div_Yield	0.010	0.076	0	0	0	0.006	0.081

This table reports summary statistics for the sample. The sample period is 1988-2010. The sample includes 247,448 firm-quarters and 766,496 firm-months. All variables are defined in Appendix III.

Panel A reports the distribution of the investment activity of the related firms ($\Delta NOA^{RELATED}$) across the 30 most populated industries of our sample. The industry classification follows the Benchmark Input-Output Surveys of the Bureau of Economic Analysis.

Panel B reports firm characteristics. The distributions of the market variables (i.e., RET, $Size$, $Momentum$, $Revision$, and $Beta$) are from data pooled over firms and months, while the distributions of the accounting based variables are from data pooled over firms and quarters.

To minimize the influence of outliers, the top (bottom) one percent of observations of the variables each month are set at the 99th (1st) percentile, except for stock RET and $Size$.

Table 2
Investment activity and Future Firm Profitability (ROA)

Panel A : OLS regression for total accruals [N=274,448 firm-quarters]

$$ROA_{t+1} = \alpha + \beta_1 ROA_t + \beta_2 \Delta NOA_t + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 D\_Loss_t + \beta_6 Div\_Yield_t + \beta_7 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Coefficient	0	0.686	-0.070	0.005	0.070	-0.058	0.009	0.015	0.506
(t-statistic)	-	*29.73*	*-7.47*	*0.77*	*15.22*	*-4.52*	*2.02*	*3.75*	

Panel B : OLS regression for firm specific and common components of total accruals

$$ROA_{t+1} = \alpha + \beta_1 ROA_t + \beta_{2A} \Delta NOA_t^{FIRM} + \beta_{2B} \Delta NOA_t^{RELATED} + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 D\_Loss_t + \beta_6 Div\_Yield_t + \beta_7 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_{2A}	β_{2B}	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Coefficient	0	0.683	-0.068	-0.030	0.003	0.070	-0.058	0.008	0.014	0.507
(t-statistic)	-	*29.54*	*-7.53*	*-4.70*	*0.40*	*14.92*	*-4.51*	*1.90*	*3.12*	
Test statistic on $\beta_{2A} = \beta_{2B}$			**-4.95**							

Panel C : OLS regression for firm specific, peers and non-peers components of total accruals

$$ROA_{t+1} = \alpha + \beta_1 ROA_t + \beta_{2A} \Delta NOA_t^{FIRM} + \beta_{2B\_1} \Delta NOA_t^{PEERS} + \beta_{2B\_2} \Delta NOA_t^{NON-PEERS} + \beta_3 BTM_t + \beta_4 Size_t + \beta_5 D\_Loss_t + \beta_6 Div\_Yield_t + \beta_7 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_{2A}	β_{2B_1}	β_{2B_2}	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Coefficient	0	0.681	-0.067	-0.026	-0.018	0.002	0.070	-0.057	0.008	0.015	0.508
(t-statistic)	-	*29.31*	*-7.61*	*-4.36*	*-3.69*	*0.18*	*14.83*	*-4.48*	*1.85*	*3.37*	
Test statistic on $\beta_{2A} = \beta_{2B\_1}$			**-5.70**								
Test statistic on $\beta_{2A} = \beta_{2B\_2}$			**-5.67**								

Panel D : OLS regression for the accrual decomposition

$$ROA_{t+1} = \alpha + \beta_1 ROA_t + \beta_2 \Delta WC_t + \beta_3 \Delta NCO_t + \beta_4 BTM_t + \beta_5 Size_t + \beta_6 D\_Loss_t + \beta_7 Div\_Yield_t + \beta_8 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	Adj. R^2
Coefficient	0	0.687	-0.043	-0.054	0.005	0.070	-0.059	0.011	0.015	0.507
(t-statistic)	-	*29.59*	*-11.27*	*-5.95*	*0.90*	*15.03*	*-4.66*	*2.43*	*3.65*	

Panel E : OLS regression for the firm specific and common component of the accrual decomposition

$$ROA_{t+1} = \alpha + \beta_1 ROA_t + \beta_{2A} \Delta WC_t^{FIRM} + \beta_{2B} \Delta WC_t^{RELATED} + \beta_{3A} \Delta NCO_t^{FIRM} + \beta_{3B} \Delta NCO_t^{RELATED} + \beta_4 BTM_t$$
$$+ \beta_5 Size_t + \beta_6\ D\_Loss_t + \beta_7 Div\_Yield_t + \beta_8 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_{2A}	β_{2B}	β_{3A}	β_{3B}	β_4	β_5	β_6	β_7	β_8	Adj. R^2
Coefficient	0	0.683	-0.043	-0.002	-0.052	-0.028	0.002	0.070	-0.058	0.010	0.014	0.509
(t-statistic)	-	*29.39*	*-11.56*	*-0.45*	*-5.96*	*-4.28*	*0.28*	*14.65*	*-4.61*	*2.23*	*2.95*	
Test statistic on $\beta_{2A} = \beta_{2B}$				**-10.89**								
Test statistic on $\beta_{3A} = \beta_{3B}$				**-3.14**								

Panel F : OLS regressions for the firm specific, peers and non-peers components of the accrual decomposition

$$\begin{aligned} ROA_{t+1} = a + \beta_1 ROA_t \\ + \beta_{2A}\Delta WC_t^{FIRM} + \beta_{2B_1}\Delta WC_t^{PEERS} + \beta_{2B_2}\Delta WC_t^{NON-PEERS} \\ + \beta_{3A}\Delta NCO_t^{FIRM} + \beta_{3B_1}\Delta NCO_t^{PEERS} + \beta_{3B_2}\Delta NCO_t^{NON-PEERS} \\ + \beta_4 BTM_t + \beta_5 Size_t + \beta_6 D\_Loss_t + \beta_7 Div\_Yield_t + \beta_8 RET_t^{RELATED} + e_{t+1} \end{aligned}$$

	α	β_1	β_{2A}	β_{2B_1}	β_{2B_2}	β_{3A}	β_{3B_1}	β_{3B_2}	β_4	β_5	β_6	β_7	β_8	**Adj. R^2**
Coefficient	0	0.681	-0.042	-0.006	0.002	-0.052	-0.023	-0.018	-0.000	0.070	-0.056	0.010	0.015	0.510
(t-statistic)	-	*29.26*	*-11.41*	*-1.33*	*0.77*	*-6.08*	*-4.44*	*-3.32*	*-0.04*	*14.56*	*-4.54*	*2.11*	*3.17*	

Test statistic on $\beta_{2A} = \beta_{2B\_1}$	**-7.46**	**Test statistic on $\beta_{2A} = \beta_{2B\_2}$**	**-10.25**
Test statistic on $\beta_{3A} = \beta_{3B\_1}$	**-3.62**	**Test statistic on $\beta_{3A} = \beta_{3B\_2}$**	**-3.81**

The reported regression coefficients are the mean of the standardized coefficients $\left(\beta_i = \beta_{i\_RAW} * \frac{\sigma_{Xi}}{\sigma_Y}\right)$ from quarterly cross sectional regressions. Each cross-sectional regression is estimated using weighted least squares where the weights are the natural log of the securities market capitalization.The *t*-statistics reported in parentheses below coefficient estimates are based on the standard errors of the coefficient estimates across the quarterly regressions. The test statistics reported at the bottom of panels B, C, E and F are the mean difference in the coefficients relative to the standard error of that mean difference across the quarterly regressions. There is no intercept in these regressions as we report standardized regression coefficients.

To minimize the influence of outliers, each quarter, the top and bottom one percent of the variables with the exception of *Size* and *RET*, were set to the 99th and 1st percentile.

All variables are defined in Appendix III.

Table 3 Investment Activity and Future Stock Returns

Panel A : OLS regressions for total accruals [N=766,496 firm-months]

$$RET_{t+1} = \alpha + \beta_1 RET_t + \beta_2 \Delta NOA_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Beta_t + \beta_6 Size_t + \beta_7 Momentum_t + \beta_8 D\_Loss_t + \beta_9 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	Adj. R^2
Coefficient	0	-0.047	-0.025	0.016	0.003	0.004	-0.020	-0.006	-0.012	0.016	0.080
(t-statistic)	-	*-8.25*	*-9.81*	*2.91*	*0.97*	*1.30*	*-4.29*	*-1.08*	*-1.58*	*5.33*	

Panel B : OLS regressions for firm specific and common components of total accruals

$$RET_{t+1} = \alpha + \beta_1 RET_t + \beta_{2A} \Delta NOA_t^{FIRM} + \beta_{2B} \Delta NOA_t^{RELATED} + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Beta_t + \beta_6 Size_t + \beta_7 Momentum_t + \beta_8 D\_Loss_t + \beta_9 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_{2A}	β_{2B}	β_3	β_4	β_5	β_6	β_7	β_8	β_9	Adj. R^2
Coefficient	0	-0.047	-0.025	-0.008	0.016	0.002	0.005	-0.020	-0.005	-0.013	0.017	0.082
(t-statistic)	-	*-8.34*	*-9.92*	*-2.01*	*3.01*	*0.94*	*1.35*	*-4.32*	*-0.99*	*-1.72*	*5.65*	
Test statistic on $\beta_{2A} = \beta_{2B}$				**-5.58**								

Panel C : OLS regression for firm specific, peers and non-peers components of total accruals

$$RET_{t+1} = \alpha + \beta_1 RET_t + \beta_{2A} \Delta NOA_t^{FIRM} + \beta_{2B\_1} \Delta NOA_t^{PEERS} + \beta_{2B\_2} \Delta NOA_t^{NON-PEERS} + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Beta_t + \beta_6 Size_t + \beta_7 Momentum_t + \beta_8 D\_Loss_t + \beta_9 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_{2A}	β_{2B_1}	β_{2B_2}	β_3	β_4	β_5	β_6	β_7	β_8	β_9	Adj. R^2
Coefficient	0	-0.047	-0.025	-0.007	-0.004	0.016	0.003	0.005	-0.020	-0.005	-0.013	0.018	0.082
(t-statistic)	-	*-8.38*	*-9.94*	*-2.42*	*-1.44*	*3.01*	*0.95*	*1.36*	*-4.30*	*-1.04*	*-1.72*	*5.67*	
Test statistic on $\beta_{2A} = \beta_{2B\_1}$				**-6.60**			**Test statistic on $\beta_{2A} = \beta_{2B\_2}$**				**-6.89**		

Panel D : OLS regressions for the accrual decomposition

$$RET_{t+1} = \alpha + \beta_1 RET_t + \beta_2 \Delta WC_t + \beta_3 \Delta NCO_t + \beta_4 BTM_t + \beta_5 NI/P_t + \beta_6 Beta_t + \beta_7 Size_t + \beta_8 Momentum_t + \beta_9 D\_Loss_t + \beta_{10} RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	**Adj. R^2**
Coefficient	0	-0.047	-0.022	-0.015	0.016	0.004	0.005	-0.021	-0.006	-0.013	0.016	0.080
(t-statistic)	-	*-8.24*	*-8.34*	*-7.80*	*2.91*	*1.05*	*1.32*	*-4.38*	*-1.09*	*-1.80*	*5.25*	

Panel E : OLS regressions for the firm specific and common component of the accrual decomposition

$$RET_{t+1} = \alpha + \beta_1 RET_t + \beta_{2A} \Delta WC_t^{FIRM} + \beta_{2B} \Delta WC_t^{RELATED} + \beta_{3A} \Delta NCO_t^{FIRM} + \beta_{3B} \Delta NCO_t^{RELATED} + \beta_4 BTM_t + \beta_5 NI/P_t + \beta_6 Beta_t + \beta_7 Size_t + \beta_8 Momentum_t + \beta_9 D\_Loss_t + \beta_{10} RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_{2A}	β_{2B}	β_{3A}	β_{3B}	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	**Adj. R^2**
Coefficient	0	-0.047	-0.022	-0.006	-0.015	-0.004	0.016	0.004	0.005	-0.021	-0.005	-0.014	0.017	0.083
(t-statistic)	-	*-8.32*	*-8.72*	*-1.66*	*-7.92*	*-0.67*	*3.00*	*1.07*	*1.36*	*-4.38*	*-1.04*	*-1.99*	*5.37*	
Test statistic on $\beta_{2A} = \beta_{2B}$				**-5.34**				**Test statistic on $\beta_{3A} = \beta_{3B}$**			**-3.43**			

Panel F : OLS regressions for the firm specific, peers and non-peers components of the accrual decomposition

$$RET_{t+1} = \alpha + \beta_1 RET_t + \beta_{2A} \Delta WC_t^{FIRM} + \beta_{2B\_1} \Delta WC_t^{PEERS} + \beta_{2B\_2} \Delta WC_t^{NON-PEERS} + \beta_{3A} \Delta NCO_t^{FIRM} + \beta_{3B\_1} \Delta NCO_t^{PEERS} + \beta_{3B\_2} \Delta NCO_t^{NON-PEERS} + \beta_4 BTM_t + \beta_5 NI/P_t + \beta_6 Beta_t + \beta_7 Size_t + \beta_8 Momentum_t + \beta_9 D\_Loss_t + \beta_{10} RET_t^{RELATED} + e_{t+1}$$

	β_{2A}	β_{2B_1}	β_{2B_2}	β_{3A}	β_{3B_1}	β_{3B_2}	**Adj. R^2**
Coefficient	-0.021	-0.002	-0.004	-0.015	-0.007	0.001	0.084
(t-statistic)	*-8.71*	*-0.79*	*-1.04*	*-7.83*	*-2.07*	*0.16*	

Test statistic on $\beta_{2A} = \beta_{2B\_1}$	**-6.79**	**Test statistic on $\beta_{2A} = \beta_{2B\_2}$**	**-5.96**
Test statistic on $\beta_{3A} = \beta_{3B\_1}$	**-2.81**	**Test statistic on $\beta_{3A} = \beta_{3B\_2}$**	**-4.78**

The reported regression coefficients are the mean of the standardized coefficients $\left(\boldsymbol{\beta}_{\boldsymbol{i}} = \boldsymbol{\beta}_{\boldsymbol{i\_RAW}} * \frac{\boldsymbol{\sigma_{Xi}}}{\boldsymbol{\sigma_Y}}\right)$ from monthly cross sectional regressions. Each cross-sectional regression is estimated using weighted least squares where the weights are the natural log of the securities market capitalization.The *t*-statistics reported in parentheses below coefficient estimates are based on the standard errors of the coefficient estimates across the monthly regressions. The test statistics reported at the bottom of panels B, C, E and F are the mean difference in the coefficients relative to the standard error of that mean difference across the monthly regressions. There is no intercept in these regressions as we report standardized regression coefficients.

To minimize the influence of outliers, each month, the top and bottom one percent of the variables with the exception of $Size$ and RET, were set to the 99th and 1st percentile.

All variables are defined in Appendix III.

Table 4 Portfolio Analyses

(First sorting on $\Delta NOA^{RELATED}$ then sorting on ΔNOA^{FIRM})

Panel A: Total Monthly Returns

		$\Delta NOA^{RELATED}$						
		LO	**2**	**3**	**4**	**HI**	**HI-LO**	**T-stat**
ΔNOA^{FIRM}	**LO**	2.62%	2.37%	2.53%	2.38%	2.41%	-0.21%	-0.59
	2	2.10%	1.61%	1.65%	1.64%	1.55%	-0.55%	-1.67
	3	1.62%	1.18%	1.36%	1.40%	1.23%	-0.39%	-1.41
	4	1.34%	1.30%	1.06%	1.20%	1.01%	-0.34%	-1.33
	HI	1.05%	0.84%	0.74%	0.51%	0.50%	-0.55%	-1.91
	HI-LO	-1.57%	-1.53%	-1.79%	-1.9%	-1.91%		
	T-stat	-6.65	-7.34	-7.42	-7.24	-7.32		

Panel B: Characteristic Adjusted Returns

		$\Delta NOA^{RELATED}$						
		LO	**2**	**3**	**4**	**HI**	**HI-LO**	**T-stat**
ΔNOA^{FIRM}	**LO**	1.40%	1.23%	1.33%	1.39%	1.39%	-0.01%	-0.04
	2	0.99%	0.43%	0.51%	0.56%	0.54%	-0.45%	-1.44
	3	0.54%	0.14%	0.37%	0.41%	0.23%	-0.31%	-1.17
	4	0.28%	0.28%	0.03%	0.19%	0.07%	-0.21%	-0.86
	HI	0.08%	-0.15%	-0.25%	-0.28%	-0.32%	-0.39%	-1.42
	HI-LO	-1.32%	-1.38%	-1.59%	-1.67%	-1.70%		
	T-stat	-5.92	-6.57	-6.81	-6.67	-6.47		

Panel C: 4-factor 'alpha'

		$\Delta NOA^{RELATED}$						
		LO	**2**	**3**	**4**	**HI**	**HI-LO**	**T-stat**
ΔNOA^{FIRM}	**LO**	1.62%	1.52%	1.71%	1.58%	1.57%	-0.05%	-0.15
		5.32	6.57	6.69	5.10	5.19		
	2	1.03%	0.66%	0.75%	0.82%	0.67%	-0.36%	-1.09
		4.22	4.55	4.36	4.28	3.32		
	3	0.61%	0.31%	0.46%	0.58%	0.45%	-0.16%	-0.60
		3.48	2.55	3.31	3.74	2.33		
	4	0.41%	0.42%	0.20%	0.43%	0.23%	-0.19%	-0.72
		2.44	2.95	1.23	2.20	1.30		
	HI	0.17%	-0.05%	-0.16%	-0.25%	-0.32%	-0.49%	-1.69
		0.84	-0.30	-0.88	-1.09	-1.62		
	HI-LO	-1.45%	-1.57%	-1.87%	-1.83%	-1.89%		
	T-stat	-6.38	-7.67	-7.95	-7.43	-7.23		

For each month stocks are first sorted into five equal groups based on the level of the investment activity of the related firms ($\Delta NOA^{RELATED}$). Then, within each group, stocks are further sorted into five groups based on the firm's idiosyncratic investment activity (ΔNOA^{FIRM}).

Panel A reports average size weighted monthly total returns from forming portfolios each month. The reported t-statistics are the mean return differences between returns for the high and low portfolios indicated relative to the standard error of that mean estimated from the time series of return differences.

Panel B is the same as panel A, except returns are characteristic adjusted following Daniel, Grinblatt, Titman and Wermers (1997). DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

Panel C reports intercepts (with t-statistics in parenthesis) from regressing portfolio monthly excess returns (over the return on the U.S. one-month Treasury bill) in the time-series regressions on excess returns associated with market (MKT), size (SMB), book-to-price (HML) and momentum (UMD) factors. The factor returns for MKT, SMB, HML and UMD factors and the one-month Treasury return were obtained from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

Table 5 Investment Activity and Future Analyst Forecast Revisions

Panel A : OLS regressions for total accruals [N=344,624 firm-months]

$$\boldsymbol{Revision_{t+1} = \alpha + \beta_1 Revision_t + \beta_2 \Delta NOA_t + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + \beta_6 D\_Loss_t + \beta_7 RET_t^{RELATED} + e_{t+1}}}$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Coefficient	0	0.025	-0.020	-0.026	-0.036	0.118	0.059	0.014	0.071
(t-statistic)	-	*2.84*	*-5.88*	*-5.50*	*-4.81*	*18.46*	*7.36*	*5.00*	

Panel B : OLS regressions for firm specific and common components of total accruals

$$\boldsymbol{Revision_{t+1} = \alpha + \beta_1 Revision_t + \beta_{2A} \Delta NOA_t^{FIRM} + \beta_{2B} \Delta NOA_t^{RELATED} + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + \beta_6 D\_Loss_t + \beta_7 RET_t^{RELATED} + e_{t+1}}}$$

	α	β_1	β_{2A}	β_{2B}	β_3	β_4	β_5	β_6	β_7	Adj. R^2
Coefficient	0	0.025	-0.020	-0.005	-0.026	-0.036	0.118	0.059	0.014	0.071
(t-statistic)	-	*2.81*	*-6.03*	*-1.27*	*-5.61*	*-4.78*	*18.42*	*7.44*	*4.94*	
Test statistic on $\beta_{2A} = \beta_{2B}$				***-4.82***						

Panel C : OLS regression for firm specific, peers and non-peers components of total accruals

$$\boldsymbol{Revision_{t+1} = \alpha + \beta_1 Revision_t + \beta_{2A}\Delta NOA_t{}^{FIRM} + \beta_{2B\_1}\Delta NOA_t{}^{PEERS} + \beta_{2B\_2}\Delta NOA_t{}^{NON-PEERS} + \beta_3 BTM_t + \beta_4 NI/P_t + \beta_5 Momentum_t + \beta_6 D\_Loss_t + \beta_7 RET_t{}^{RELATED} + e_{t+1}}$$

	α	β_1	β_{2A}	β_{2B_1}	β_{2B_2}	β_3	β_4	β_5	β_6	β_7	**Adj. R^2**
Coefficient	0	0.025	-0.020	-0.004	-0.004	-0.026	-0.036	0.117	0.059	0.015	0.072
(t-statistic)	-	*2.81*	*-6.06*	*-1.21*	*-1.18*	*-5.70*	*-4.84*	*18.40*	*7.47*	*4.98*	
Test statistic on $\beta_{2A} = \beta_{2B\_1}$				**-5.39**			**Test statistic on $\beta_{2A} = \beta_{2B\_2}$**			**-4.89**	

Panel D : OLS regressions for the accrual decomposition

$$\boldsymbol{Revision_{t+1} = \alpha + \beta_1 Revision_t + \beta_2 WC_t + \beta_3 NCO_t + \beta_4 BTM_t + \beta_5 NI/P_t + \beta_6 Momentum_t + \beta_7 D\_Loss_t + \beta_8 RET_t{}^{RELATED} + e_{t+1}}$$

	α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	**Adj. R^2**
Coefficient	0	0.026	-0.020	-0.012	-0.026	-0.036	0.118	0.058	0.012	0.072
(t-statistic)	-	*2.97*	*-5.80*	*-4.13*	*-5.73*	*-4.61*	*18.13*	*7.32*	*4.50*	

Panel E : OLS regressions for the firm specific and common component of the accrual decomposition

$$Revision_{t+1} = \alpha + \beta_1 Revision_t + \beta_{2A}\Delta WC_t^{FIRM} + \beta_{2B}\Delta WC_t^{RELATED} + \beta_{3A}\Delta NCO_t^{FIRM} + \beta_{3B}\Delta NCO_t^{RELATED} + \beta_4 BTM_t + \beta_5 NI/P_t + \beta_6 Momentum_t + \beta_7 D\_Loss_t + \beta_8 RET_t^{RELATED} + e_{t+1}$$

	α	β_1	β_{2A}	β_{2B}	β_{3A}	β_{3B}	β_4	β_5	β_6	β_7	β_8	Adj. R^2
Coefficient	0	0.026	-0.020	-0.002	-0.012	-0.005	-0.027	-0.036	0.118	0.059	0.012	0.073
(t-statistic)	-	*2.92*	*-6.61*	*-0.93*	*-4.20*	*-0.73*	*-5.85*	*-4.58*	*18.03*	*7.47*	*4.25*	
Test statistic on $\beta_{2A} = \beta_{2B}$				**-5.67**			**Test statistic on $\beta_{3A} = \beta_{3B}$**				**-2.16**	

Panel F : OLS regressions for the firm specific, peers and non-peers components of the accrual decomposition

$$Revision_{t+1} = \alpha + \beta_1 Revision_t + \beta_{2A}\Delta WC_t^{FIRM} + \beta_{2B\_1}\Delta WC_t^{PEERS} + \beta_{2B\_2}\Delta WC_t^{NON-PEERS} + \beta_{3A}\Delta NCO_t^{FIRM} + \beta_{3B\_1}\Delta NCO_t^{PEERS} + \beta_{3B\_2}\Delta NCO_t^{NON-PEERS} + \beta_4 BTM_t + \beta_5 NI/P_t + \beta_6 Momentum_t + \beta_7 D\_Loss_t + \beta_8 RET_t^{RELATED} + e_{t+1}$$

	β_{2A}	β_{2B_1}	β_{2B_2}	β_{3A}	β_{3B_1}	β_{3B_2}	Adj. R^2
Coefficient	-0.019	-0.002	-0.001	-0.013	-0.006	-0.005	0.074
(t-statistic)	*-6.60*	*-0.76*	*-0.86*	*-4.24*	*-1.98*	*-0.80*	

Test statistic on $\beta_{2A} = \beta_{2B\_1}$	**-5.41**	**Test statistic on $\beta_{2A} = \beta_{2B\_2}$**	**-5.56**
Test statistic on $\beta_{3A} = \beta_{3B\_1}$	**-2.12**	**Test statistic on $\beta_{3A} = \beta_{3B\_2}$**	**-2.14**

The reported regression coefficients are the mean of the standardized coefficients $\left(\beta_i = \beta_{i\_RAW} * \frac{\sigma_{Xi}}{\sigma_Y}\right)$ from monthly cross sectional regressions. Each cross-sectional regression is estimated using weighted least squares, where the weights are the natural log of the securities market capitalization.The *t*-statistics reported in parentheses below coefficient estimates are based on the standard errors of the coefficient estimates across the quarterly regressions. The test statistics reported at the bottom of panels B, C, E and F are the mean difference in the coefficients relative to the standard error of that mean difference across the quarterly regressions. There is no intercept in these regressions as we report standardized regression coefficients.

To minimize the influence of outliers, each month, the top and bottom one percent of the variables, with the exception of RET, are set to the 99^{th} and 1^{st} percentile.

All variables are defined in Appendix III.

Table 6

Return Correlation Structure across ΔNOA portfolios

	LOW	2	3	4	5	6	7	8	9	HIGH
LOW	**0.103**	0.104	0.103	0.101	0.102	0.103	0.105	0.107	0.109	0.109
2	0.104	**0.109**	0.109	0.109	0.111	0.111	0.113	0.115	0.116	0.115
3	0.103	0.109	**0.113**	0.114	0.115	0.116	0.117	0.119	0.119	0.116
4	0.101	0.109	0.114	**0.116**	0.119	0.119	0.119	0.121	0.121	0.118
5	0.102	0.111	0.115	0.119	**0.121**	0.122	0.123	0.125	0.124	0.120
6	0.103	0.111	0.116	0.119	0.122	**0.123**	0.124	0.126	0.125	0.122
7	0.105	0.113	0.117	0.119	0.123	0.124	**0.125**	0.128	0.128	0.124
8	0.107	0.115	0.119	0.121	0.125	0.126	0.128	**0.131**	0.131	0.128
9	0.109	0.116	0.119	0.121	0.124	0.125	0.128	0.131	**0.132**	0.130
HIGH	0.109	0.115	0.116	0.118	0.120	0.122	0.124	0.128	0.130	**0.129**

Each month stocks are sorted into ten equal groups based on ΔNOA. We then compute the pairwise correlation in stock returns for the following twelve months for every security in each ΔNOA portfolio with every other security in (i) the same portfolio, and (ii) other ΔNOA portfolios. We take the average cross-sectional pairwise correlation for the resulting 100 combinations and average those cross-sectional pairwise correlations across our 272 months. The table above reports these global average pairwise correlations. The diagonal elements represent the average stock return correlations within ΔNOA portfolios and the off-diagonal elements represent the average stock return correlations across ΔNOA portfolios. The shading of cells reflects the strength of the correlation with lighter (darker) reflecting lower (higher) correlations.